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# Comparing Fence Modeling and Mapping Approaches to Support Wildlife Management and Research in Southwest Montana

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# COMPARING FENCE MODELING AND MAPPING APPROACHES TO SUPPORT WILDLIFE MANAGEMENT AND RESEARCH IN SOUTHWEST MONTANA

By

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Comparing fence modeling and mapping approaches to support wildlife management and research in southwest Montana

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Fences pose significant challenges to wildlife movement, but their effects are difficult to quantify because fence location and fence type data are lacking on a global scale. We developed a fence location and density model in southwest Montana, USA to provide data to researchers and managers, and test whether previous models could be applied to a new region and retain suitable levels of statistical accuracy. Our model used local expert opinion to inform how road, land cover, and ownership spatial layers interacted to predict fence locations. We validated the model against fence data collected on random 3.2 km road transects (n = 330). The model predicted 37,687 km of fences across the study area, with a mean fence density of 1.6 km/km$^2$ and a maximum density of 11.3 km/km$^2$. Additionally, we manually digitized fences in Google Earth Pro in a random sample of 50 survey townships (roughly 4,650 km$^2$) within the study area and validated the accuracy of this method to compare results against the fence model predictions. Our fence model showed lower agreement (Cohen's Kappa = 0.56) with known samples than manually-digitized fences in Google Earth (Cohen's Kappa = 0.76), yet had an improved level of accuracy over previous models. The fence model outputs are likely most useful for large scale analyses of ecological influences of fence densities, whereas the Google Earth digitizing method is likely useful to locate individual fences for fine-scale analyses. While the Google Earth approach is highly accurate in open landscapes, it is significantly more time intensive than the modeling approach and so the cost-benefit between methods must be considered. We demonstrate the utility of our Google Earth fence mapping technique using recently collected pronghorn (*Antilocapra americana*) movement data. The restricted movements of pronghorn interacting with fences support our finding that fences in our study area, regardless of whether they were located on public or private lands, can act as barriers to wildlife. Our results provide options for mapping fences at multiple scales and elucidate a need for fence modifications on both public and private lands to facilitate wildlife movement requirements and improve ecological connectivity.

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# Contents

# Introduction

Human communities have been erecting fences and other barriers throughout history. Early European settlers to North America built fences out of readily available materials such as wood and stone to corral livestock and protect crops (Hayter 1939). During the American Civil War, the US government spurred western expansion through policies such as the Homestead Act of 1862, which allowed citizens to claim land and ushered white settlers into the Great Plains and beyond. Demand grew for new technologies as wood and stone fences became impractical across the grass prairies of the west (Hayter 1939). In the late 19$^{th}$ century, advancements in metallurgy and marketing led to the mass production and distribution of low-cost and effective barbed wire fencing (Hayter 1939, Krell 2002, Bennett and Abbott 2014). Barbed wire was both an economic and cultural tool that transformed the American West, displacing native peoples and wildlife and manifesting private property rights and capitalism across the landscape (Netz 2004). The application of barbed wire fences to delineate property rights in the American West was a major factor in creating the economic and legal structures that continue to govern access to natural resources such as land, water, and public grazing areas (Libecap 2007). In this respect, barbed wire fencing has become a ubiquitous and core component of the landscape in western North America (Jakes et al. 2018*a*).

Despite widespread adoption and continued construction of fences, there remains limited understanding of their spatial distribution, types, and effects on wildlife populations and ecological processes (Jakes et al. 2018*a*). Fences may be judged as having positive or negative effects on ecological processes depending on the species or ecosystem under consideration (McInturff et al. 2020). For example, fences have been used extensively to protect endemic species and sensitive habitats from invasive species (Katahira et al. 1993, Moseby and Read

2006, Young et al. 2013). However, fencing is more abundant than roads in many areas and therefore represents a major anthropogenic feature that has received comparatively little ecological attention (Jakes et al. 2018*a*). Biodiversity continues to decline globally due to anthropogenic disturbances such as fragmentation and habitat loss (Haddad et al. 2015), and these effects are compounded as species' vagility is dampened due to human activities (Tucker et al. 2018). In this regard, fences are an important consideration to include in connectivity, habitat, and demographic analyses on a global scale (Jakes et al. 2018*a*, McInturff et al. 2020).

The effects of fences on wildlife populations can be profound, though few studies have specifically evaluated these effects. Fences can pose direct risks of entanglement to ungulate populations that daily and seasonally traverse a matrix of land ownership, potentially resulting in injury or death (Harrington and Conover 2006, Rey et al. 2012). Fence effects on ungulates can also be indirect, such as reducing forage availability and causing behavioral changes during migration, which likely impact overall fitness (Sawyer et al. 2009, Sawyer and Kauffman 2011, Jones 2014, Seidler et al. 2015, Jones et al. 2019). Furthermore, fence specifications that completely restrict ungulate movement can contribute to population declines as animals may be prevented from tracking seasonal shifts in resources (Whyte 1988). In addition, the location and type of fences are major factors influencing collisions with fences by large, low flying birds such as sage grouse (*Centrocercus urophasianus)* (Stevens et al. 2012). As fences continue to increase in number and density across the globe, they have the potential to irreparably alter ecological processes at multiple scales (Løvschal et al. 2017).

A critical challenge is that fence location data is lacking and there are no standardized approaches to assessing where fences are across the landscape and what factors determine their locations and densities (Jakes et al. 2018*a*). This lack of fence data makes it difficult to analyze the cumulative effects of fences across temporal and spatial scales for a variety of wildlife species. Modeling methods have previously been developed to predict fence locations and densities (Poor et al. 2014) for use in assessing effects to wildlife (see Jones et al. 2019). Recently, McInturff et al. (2020) followed methods from Poor et al. (2014) to map fences across parts of 10 western US states to display areas of variable fence densities within various levels of the human footprint. Using this coarse approach, southwest Montana was identified as an area of concern and mitigation opportunity with a predicted low human footprint but relatively high fence density (McInturff et al. 2020).

Here, we applied the Poor et al. (2014) fence modeling approach in two counties in southwest Montana and compared results to a fence mapping technique using Google Earth. Applying the modeling approach in a new region can contribute to identifying factors and standardizing methods to generate fence datasets on large scales. We hypothesized that fence modelling results for southwest Montana would provide similar accuracy to previous results across northern Montana (Poor et al. 2014). Additionally, we assessed which methods and parameters, when applied to new areas, were responsible for accurately modeling fence locations.

Satellite imagery has improved in resolution and availability, and we manually digitized fences using Google Earth in a portion of our study area to test the accuracy and efficacy of this approach against modeling efforts. A previous attempt to approximate fence locations by analyzing imagery and using cattle trails as a proxy for fence locations showed promising results (Seward et al. 2012). We wanted to test whether fences that are visible in modern and widely available satellite imagery software such as Google Earth could be accurately digitized on private and public lands and in a variety of land cover types. We hypothesized that the Google

Earth digitization method would have greater accuracy than the model (i.e., Kappa > 0.40), and we predicted that it would provide a fence map of greater detail for use in wildlife management and research at finer scales. We compared the cost-benefits of both approaches to determine if time requirements necessary to complete digitization would outweigh the potential gains of increased accuracy. To test the efficacy of Google Earth fence digitizing as a wildlife management tool, we mapped fences in a known pronghorn (*Antilocapra americana)* winter range area in Beaverhead County, Montana, and overlaid GPS collar data. We hypothesized that our hand-digitized fence map would help identify both the fences that allowed pronghorn passage and those that restricted movement because of their construction type.

Fence construction material and design varies with intended use. Barbed wire fences, generally constructed to contain cattle, are built using a variety of methods that may include 3-5 (or more) strands of wire spaced at different vertical intervals (H-1741-1 Range Handbook: Fencing 1989). Woven wire mesh fences are also prevalent and are generally used in husbandry of smaller-bodied animals such as sheep (H-1741-1 Range Handbook: Fencing 1989). Woven wire and electric fences, though more expensive than barbed wire, are generally more effective at excluding wildlife and are thus also used to exclude deer and other animals from depredating crops (Vercauteren et al. 2006). Because of their effectiveness, woven wire or chain-link fences are also used along highways to reduce wildlife-vehicle collisions (Clevenger et al. 2001).

The specific design of fencing determines whether it acts as an impermeable or semipermeable barrier to wildlife movement (Sheldon 2005, Burkholder et al. 2018, Jones et al. 2018). It may only take one impenetrable fence or extreme weather event to block movements completely. Wildlife movement studies have identified certain clearance requirements below and above fences to allow for wildlife passage so that animals can access forage and important seasonal range (Jones et al. 2018). Pronghorn are often used as an umbrella species for fence specification requirements in North America because they did not evolve to jump over obstacles and therefore require passing under fences (Gates et al. 2012). Thus, a 46 cm (18 in) high smooth bottom-wire and a 106 cm (40 in) high top wire have been identified as wildlife friendly fence specifications (Jones et al. 2018).

Few studies have collected baseline data on the prevalence of different fence types, and we sought to create a database for managers and researchers to use in further habitat use and movement analyses in response to fence type. For example, the prevalence and distribution of woven wire fences influenced how pronghorn selected home ranges and migration routes in Wyoming (Sheldon 2005). We also evaluated whether fence types and specifications varied between public and private lands because large populations of mule deer (*Odocoileus hemionus*), white-tailed deer (*Odocoileus virginianus*), elk (*Cervus elaphus)*, pronghorn, sage grouse, and other species traverse landownership boundaries to fulfill life cycle requirements in southwest Montana. We were also interested in determining if certain fence types were more likely to be found in certain land cover types. We tested the hypotheses that 1) there was a difference in mean bottom and top wire heights of fences on private and public lands in our study area; 2) fence type and land owner type (public or private) were independent; and 3) fence type and land cover type were independent. These assessments provide a novel dataset of actual fence characteristics that exist in our study area and may inform future fence type modeling efforts.

## Study Area

Beaverhead (14,438 km$^2$) and Madison (9,326 km$^2$) counties in Southwest Montana have an approximate total area of 23,764 km$^2$. Publicly owned land is the dominant land tenure type, comprising approximately 63% of the total landscape. The largest public land management agencies include the U.S. Forest Service (USFS), the Bureau of Land Management (BLM), and the State of Montana (Table 1). Private lands are primarily agricultural and residential, and to a lesser extent industrial or mining. Livestock ranching is widespread, and despite a general transition to beef cattle, an historic sheep ranching legacy is generally recognized as a significant contributing factor to the prevalence of woven wire fences that remain on the landscape.

The study area is bounded on the west and south by the Continental Divide, which is also the Idaho/Montana border. The geography of the area is characterized by broad intermountain grassland and sagebrush valleys framed by conifer forested mountain ranges (up to 3,450 m). The area comprises the headwaters of the Missouri River, including the Big Hole, Beaverhead, Madison, and Jefferson River watersheds. Most roads are unpaved rural county and USFS roads. Paved roads include city streets, interstate I-15, US Highway 287, and several state highways and frontage roads. The largest town is Dillon, MT with a population of 4,134 (2010).

***Table 1**: Land ownership estimates within the study area of Beaverhead and Madison counties.*

| **Landowner** | **Total Area ($Km^2$)** | **% Total Area** | **Beaverhead County ($Km^2$)** | **% Total Beaverhead** | **Madison County ($Km^2$)** | **% Total Madison** |
|---|---|---|---|---|---|---|
| US Forest Service | **8,849** | 37% | 5,571 | 39% | 3,278 | 35% |
| Private | **8,825** | 37% | 4,465 | 31% | 4,360 | 47% |
| BLM | **3,696** | 16% | 2,687 | 19% | 1,008 | 11% |
| State government | **2,118** | 9% | 1,441 | 10% | 676 | 7% |
| Other government | **277** | 1% | 274 | 2% | 3 | 0% |
| **Total** | **23,764** | | **14,438** | | **9,326** | |

# Methods

## Sampling Scheme for Data Collection

We used a combination of land cover and road data to generate a stratified random sample of point locations along roads that we used as starting points of fence transects. All spatial analyses were conducted in NAD 1983 coordinate system in ArcMap 10.6.1 (Esri 2018). We used the Montana Landcover 2016 Framework 30m resolution dataset to represent the natural and human land cover classes (Montana State Library). Land cover types were reclassified into five general categories , which included “agriculture,” “forest,” “grassland,” “riparian,” and “shrubland” (Poor et al. 2014). Non-vegetation land cover types including roads, alpine rock and ice, cliffs, open water, and human development were removed and replaced with “no data.” We interpolated land cover type for the deleted roads and then transformed the five raster classes to polygons.

We used the Montana Department of Transportation’s road layers (Montana Department of Transportation) and merged and dissolved road line segments so that each unique road was represented by a single, connected line. We then deleted roads shorter than 3.2 km as this was the standard length of our sampling transects (Poor et al. 2014). On USFS lands specifically, we retained only primary and secondary roads and deleted the multitude of minor roads.

Random points were generated every 5km along the edited road layer and served as the starting points of 3.2 km fence transects. We used a 5km distance between starting points to allow for adequate coverage of the study area, which serves as a representative sample of the road surface type/land cover type combinations. The 5km between transect starting points also allowed us to capture the differences in fence locations and types across both counties. Using this approach and subtracting random points along the interstate for safety purposes, we were left with a total of 692 transect starting points.

We gave each of the 692 transect starting points a unique identifier and intersected them with the land cover and road layers, resulting in twelve possible combinations for land cover/road surface type: NoData/Unpaved, NoData/Paved, Agriculture/Unpaved, Agriculture/Paved, Forest/Unpaved, Forest/Paved, Shrubland/Unpaved, Shrubland/Paved, Grassland/Unpaved, Grassland/Paved, Riparian/Unpaved, Riparian/Paved. We divided each of the twelve lists in half and took a random sample in R version 3.5.3 (R Core Team, 2019), without replacement, giving a total of 349 transects that could feasibly be surveyed (Appendix I).

## Sampling Protocol

We completed 330 transects from June-August 2019, surveying a total of 1,056 km along roads in Beaverhead and Madison Counties. We collected data using a hand-held Samsung Galaxy 7 tablet with the Collector app (Esri 2018). For each transect, we sampled both the fences that paralleled roads, hereafter called ‘road fences’, and fences that ran perpendicular to roads, hereafter called ‘internal fences’ (Poor et al. 2014).

At the starting point of a transect, we added a GPS point record to the road fence layer and entered attribute data for fences paralleling both sides of the road (Appendix II-A). This attribute data included fence type, maintenance level, and bottom and top wire height measurement estimates. Our estimated measurements of wire heights were conducted via visual inspection from 10-40 m away from a fence (with the aid of binoculars), so they were not exact measurements. However, we spent the first week of data collection measuring wire heights by hand with a tape measure to calibrate our visual estimations for the remaining samples. We measured each 3.2 km transect using the vehicle odometer and added additional GPS points to the road fence layer at each location where roadside fencing started, stopped, or changed type. If the fence presence, absence, or type changed on one side of the road but not the other, we only entered data for the changing side and left the other side blank to indicate no change. A road fence had to be within 100m of the road and at least 100m long to be recorded (Poor et al. 2014).

While driving a transect, we also added new GPS point records to the internal fence layer at each instance where a perpendicular fence intersected the road (Appendix II-B). We indicated on which side of the road the internal fence was located and entered the same attribute data as we did for road fences. If a fence crossed the road (e.g. at a cattleguard), we collected two internal fence points because fence attributes often changed from one side of the road to the other. An internal fence segment had to be at least 200m long to be recorded (Poor et al. 2014).

## GIS Fence Location Modeling

We developed four GIS models to test which one best predicted fence locations in our study area (Table 2). These four models represented the combinations of major assumptions gained from local experts estimating where fences were located on the landscape based on land tenure, land cover types, and roads/railways (Poor et al. 2014) (Appendix III). We retrieved publicly available data including roads, railroads, parcel ownership, federal grazing allotment boundaries, land cover, and water. We obtained additional fence location data for specific parcels from Montana Department of Natural Resources and The Nature Conservancy. The assumptions guided adjustments and GIS layer intersection using Arc Map Model Builder (Esri 2018) to create the final fence models.

We built the predictive fence location models starting with land tenure (the private and public land fence line layers) on the bottom, then added the cropland fence layer (for models 1 and 3 only), then added the combined roads and railroad fence line layer, following methods and inferences in Poor et al. 2014 (Table 2). As we added layers, we erased sections of each underlying layer where they overlapped the subsequent layer, thus forming a hierarchy (Poor et al. 2014).

All models had the same public land and road layers because we felt most confidant in these layers based on consistency in assumptions from different local experts. We changed the private land tenure and the cropland layers between models because these were the assumptions in which we had the least confidence because there were varying views from expert opinions. The four models comprised all possible combinations of the two types of private land tenure layers ('dissolved' or 'undissolved'), the public land tenure layer, the cropland layer, and the road layer.

***Table 2****: Four GIS fence models testing which combination of layers best predicted fence locations in Beaverhead and Madison Counties. The 'dissolved private land tenure' layer assumed that adjacent parcels with the same owner only had fences around the outside boundary of both contiguous parcels. 'Undissolved private land tenure' assumed all private parcel boundaries were fenced.*

| **Model** | **Predicted Fence Layers** |
|---|---|
| 1 | Dissolved private land tenure + public land tenure + croplands + roads |
| 2 | Dissolved private land tenure + public land tenure + roads |
| 3 | Undissolved private land tenure + public land tenure + croplands + roads |
| 4 | Undissolved private land tenure + public land tenure + roads |

## Land Tenure Fence Modeling

We used a private land and public land ownership layer (Montana State Library), as well as known fence locations obtained from Montana DNRC and The Nature Conservancy, as the base layers in the subsequent four models. We edited the ownership layer based on the assumptions obtained from local experts (Appendix III). For example, the 'dissolved' private land tenure layer in models 1 and 2 assumed that adjacent private parcels with the same owner had a fence around their combined outer boundary and we deleted the boundary between the parcels. The ‘undissolved’ private land tenure layer used in models 3 and 4 assumed fences were present around each separate legal private parcel, regardless of owner, and was thus labeled ‘undissolved’. We tested these two different private land tenure layers because there was not consensus among local experts regarding the locations of fences on private lands. All four models included the public land tenure layer which was constructed using primary assumptions that land boundaries and grazing allotments were fenced and that BLM allotments superseded all other public or private land delineations.

## Land Cover Fence Modeling

We used the 2019 Montana Department of Revenue Final Land Unit (FLU) classification data to create a croplands layer (Montana State Library). Opinions from local experts were inconclusive as to the location of fences in relation to other landcover types on private and public lands, so cropland fences were our only land cover assumption in the model. The FLU data are a classification of private agricultural lands into six classes, which include fallow, hay, grazing, irrigated, continuously cropped, and forest. Data are updated annually using a combination of NAIP imagery, land change classification requests from landowners, and county agriculture and forestry appraisal staff. Based on land cover assumptions, we extracted hay, irrigated, and continuously cropped polygon classes from the data and merged them together (Appendix III). For models 1 and 3, we erased these combined cropland polygons from the land tenure layers because we assumed that if a crop outline overlapped multiple land parcel divisions, only the crop outline would be fenced and not each individual parcel. We then converted the polygons to lines and merged them with the land tenure layers.

## Road & Railroad Fence Modeling

We used the same road layers for the models that we used in the GIS for data collection (Montana Department of Transportation). This database consisted only of public roads that were navigable by a passenger vehicle, so two-tracks and private ranch roads were not included. These road types were omitted because there was no way for us to ground truth them. We also removed roads in towns from this layer because the primary assumption in urban areas was that fences followed land parcel boundaries. We then created a 'primary road layer' that consisted of all major paved roads and a 'secondary road layer' that consisted of gravel roads and minor paved roads. Using local expert opinion, we assumed that all major paved roads were fenced, except for some portions in National Forest lands, and that gravel roads and minor paved roads were fenced on both sides unless traversing public lands (Appendix III).

We then buffered the primary road layer by 19m and the secondary road layer by 11m, following Poor et al. 2014, and erased these polygons from the private land tenure, cropland, and railroad layers. We then converted the buffered polygons to lines and erased BLM and USFS lands from the secondary road layer. We merged the primary and secondary line layers together and deleted the buffer end caps. The result was the complete modeled road fence line layer. There was one railroad running the length of our study area from north to south along Interstate 15 and we estimated a mean right-of-way width of 30m on each side of the track where fences were located. We buffered the railroad layer (Montana State Library) by 30m on each side and erased this polygon from the private land and cropland layers. We converted the polygon buffer to lines, deleted the end caps, and merged it with the road fence layer.

## Fence Density

Once layers were combined, we deleted wilderness areas and alpine land cover from our top model because these areas were assumed to be unfenced. We also deleted modeled fences within the city limits of Dillon and Lima in Beaverhead County and Ennis, Sheridan, Twin Bridges, and Virginia City in Madison County because fences were assumed to follow property boundaries in towns, and we did not collect ground truth data within these city limits. We then intersected the final fence layer with land ownership polygons to indicate whether a fence was located on public or private land. We did this for the final complete fence layer because road fences and cropland fences did not contain landowner data. We calculated fence density in ArcMap 10.6.1 with a search radius of 1609.344 meters (1 mile) and a cell size output of 402.336 square meters (0.1 acre) as this was an appropriate resolution for displaying fence density maps of our study area.

## Google Earth Fence Mapping

Using survey townships as the sample unit, we mapped fences in a portion of our study area with Google Earth Pro version 7.3.3 (Google 2020) to compare fence mapping. A total of 301 survey townships (complete or portions) are in Beaverhead and Madison Counties with each township approximately 93.32 $km^2$ (36 $mi^2$). Of these 301 survey townships, there were 155 that contained three or more road fence GPS points from our transect surveys. We took a simple random sample, without replacement, in R (R Core Team, 2019) of 50 from the 155 survey townships containing three or more data points (Figure 1). This ensured the subset sample of survey townships only included those that had ground truth field data present for validation.

We then traced road fences and internal fences within the 50 sample townships using imagery in Google Earth Pro. We used the road layer from our GIS fence model and traced fences that paralleled public roads within 100m of the road. Fences located further than 100m from public roads were classified as internal fences.  We only traced internal fences that were 200m or longer.  Using these two types of line categories allowed us to perform the same validation assessment that we used in evaluating the GIS fence location model with the same field data.

We only traced lines where we could identify fences (e.g. wires, posts, pickets, rails, and corner braces) unless a patch of vegetation, shadow, or another geographic feature obscured a portion of a fence.  In these instances, we estimated the location of the obscured fence section and manually drew it.  If a fence was lost completely (i.e., it did not come out the other side of a vegetation patch), we discontinued tracing it.  We did not import any field data into Google Earth Pro and so remained unbiased of the locations of transects, road fence GPS points, and internal fence GPS points.

We then calculated additional fence densities for modeled fences and manually-digitized fences from Google Earth within the sample of 50 survey townships in order to compare the density output for the two methods.  We erased forest from the two fence layers and calculated density for each township with a search radius of 330 meters and a cell size output of 30m to approximate the resolution of common land cover raster datasets.

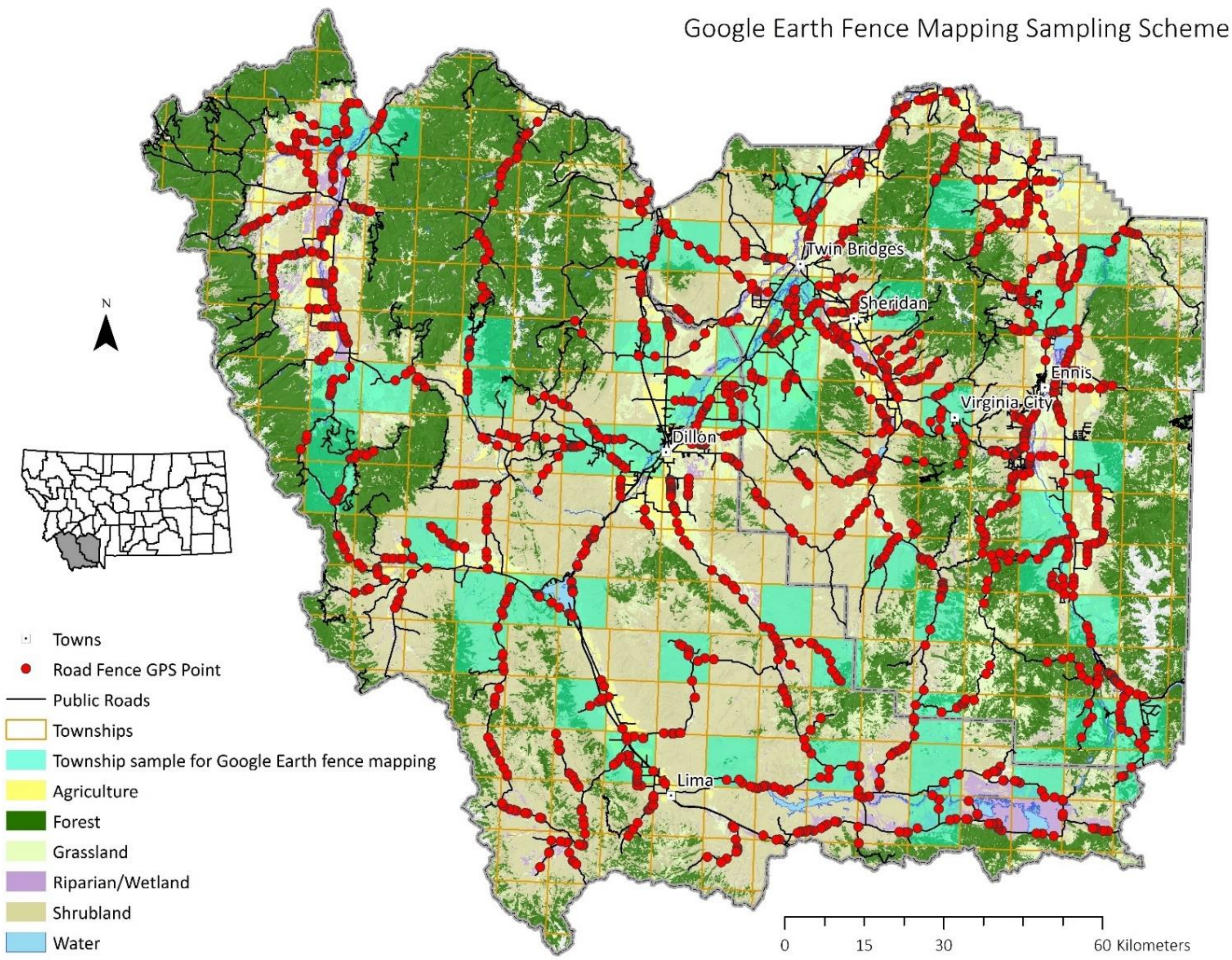


***Figure 1****: Map of Beaverhead and Madison Counties showing 50 survey townships randomly sampled for Google Earth fence mapping. Spatial reference is NAD 1983 State Plane Montana FIPS 2500.*

## Validation

We compared points along transects with modeled fencing and Google Earth mapped fencing to calculate accuracy in confusion matrices with true positives, false positives, true negatives, and false negatives.  We separately tested the accuracy of modeled and mapped fences (both road and internal), and then conducted total combined accuracy tests and Cohen's Kappa statistics for each test (Poor et al. 2014).

The Kappa statistic tests the agreement between the predictions and ground-truth data while accounting for agreement due to chance, and takes the form:

$$K = \frac{p_o - p_c}{1 - p_c}$$

Where K is the coefficient of agreement, $p_o$ is the observed accuracy, and $p_c$ is the accuracy expected by chance (Cohen 1960). Although the Kappa statistic was originally designed in a medical diagnostic setting, it has since been adopted to measure accuracy in remote sensing land cover classifications (Fisher et al. 2018). This type of application is similar to our fence location modeling and mapping efforts, and so makes Kappa an appropriate statistic to use in validation (Poor et al. 2014).

The value of K ranges from -1 to 1, where 1 represents complete agreement, 0 represents agreement equal to chance, and negative values represent agreement less than chance (Cohen 1960). Landis and Koch, 1977 suggest dividing Kappa scores into further categories to better describe their strength of agreement that have become widely adopted as standards for discussion (Landis and Koch 1977). We calculated K and confidence intervals in R version 3.5.3 (R Core Team 2019) with the 'fmsb' package (Nakazawa, 2018), to test the null hypothesis that agreement was equal to chance and K = 0. We also evaluated the sensitivity (ability to detect true positives) and specificity (ability to detect true negatives) of each accuracy test for each model. We sought high values that were balanced between these two characteristics when evaluating model results.

## Road Fence Validation

We first divided fence transects into lines that contained fence attributes from our field data GPS points. This allowed us to calculate total lengths of sampled road fence types and generate random points on fenced and unfenced portions of each transect for use in validation. We labeled transect line segments that were fenced on at least one side of the road as ‘fenced’ and labeled transect segments as ‘unfenced’ if they had no roadside fencing on either side of the road (Poor et al. 2014). Next, we generated random points along all transects with a minimum of 100m distance between points to avoid overlap and labeled them as ‘fenced’ or ‘unfenced’ based on their position on the transect line segments. We then buffered points by 30m to account for spatial error (Poor et al. 2014).

We then buffered our modeled road fence layer and our mapped Google Earth road fence layer by 30m to account for spatial error and joined them to the ‘fenced’ and ‘unfenced’ random point buffers (Poor et al. 2014). ‘Fenced’ points that overlapped our modeled or mapped road fences were true positives, and ‘unfenced’ points that did not overlap our modeled or mapped road fences were true negatives. ‘Unfenced’ points that overlapped our modeled or mapped road fences were false positives, and ‘fenced’ points that did not overlap our modeled or mapped road fences were false negatives.

## Internal Fence Validation

We isolated and buffered the endpoints of modeled internal fences and the mapped internal Google Earth fences by 30m to account for spatial error (Poor et al. 2014). To find true positives, we found where buffered internal fence GPS points that we collected along road transects overlapped these buffered endpoints. To identify false positives, we generated random points along the road transects that were not coincident with the internal fence GPS points, buffered them by 30m, and found where they overlapped the modeled/mapped internal fence endpoints. True negatives were identified as random points along transects that did not overlap the modeled/mapped internal fence endpoints. False negatives were identified as buffered internal fence GPS points collected along road transects that did not overlap modeled/mapped internal fence endpoints.

### Total Fence Validation

To assess the total fence accuracy for each method, we combined the modeled (or mapped) road fence layer with the modeled (or mapped) internal fence layer and buffered this overall layer by 30m to account for spatial error (Poor et al. 2014). We then buffered all fenced points along transects by 30m. True positives occurred where these points overlapped the complete buffered fence model/map. We then generated random points along transect segments that were at least 30m away from road fence points and internal fence points. True negatives were found where these unfenced points did not overlap modeled/mapped fences. False positives were found where these unfenced points overlapped the modeled/mapped fencing. False negatives occurred where road and internal fence point buffers along transects did not overlap modeled/mapped fences.

## Fence Type Summary and Analysis

The two classes of fences (road fences and internal fences) were measured using different units. The road fences were measured in length (km) and the internal fences were measured by point locations of their intersections with roads. The single point locations of internal fence were easier to compare to one another in statistical analyses. We tested the hypotheses that 1) there was a difference in mean bottom and top wire heights of internal fences on private and public lands in our study area; 2) internal fence type and land owner type (public or private) were independent; and 3) internal fence type and land cover type were independent. We used the same five reclassified classes of land cover from the Montana Landcover 2016 Framework that we used to generate the stratified random sample of road transect starting points (Montana State Library). We also used the same public and private landowner layer that we used to model land tenure fences in our models (Montana State Library).

### Bottom Wire Height of Internal Fences on Private v. Public Lands

We compared the estimated bottom wire heights from the ground for sampled internal fences located on private lands ($n_1$ = 1130) versus sampled internal fences located on public lands ($n_2$ = 242). Both sample data were randomly sampled, and we assumed independence between the samples because all internal fence GPS points were classified as either public or private (i.e. there were no points that could be classified as both). Our classification points occurred only at roads, and it is possible that fences crossed ownership beyond roads. We confirmed that both sample distributions were approximately normally distributed by using Q-Q Plots in R ("ggplot" package). We also confirmed that neither sample had extreme outliers (values above $Q_3 + 3 \times IQR$ or below $Q_1 - 3 \times IQR$).

Because we did not know the true population standard deviations ($\sigma_1$and $\sigma_1$) nor the true population means ($\mu_1$ and $\mu_2$), we used the sample standard deviations ($s_1$and $s_2$) and the sample means ($\bar{y}_1$and $\bar{y}_2$) to conduct a two-sided Welch's Two Sample T-test with 95% confidence intervals on the sample means to test if there was a difference between the means on private and public lands. Analyses were conducted in R version 3.5.3 (R Core Team, 2019).

### Top Wire Fence Heights on Private v. Public Lands

We compared the estimated top wire heights from the ground for sampled internal fences located on private lands ($n_3$ = 1130) versus sampled internal fences located on public lands ($n_4$ = 242). Data exploration indicated that private and public internal fence top wire height sample distributions were both skewed and contained many outliers. We therefore conducted inferences on the sample medians ($m_1$ and $m_2$). We used a non-parametric Wilcoxon rank sum test in R using the 'rstatix' package (Kassambara, 2020) to test if there was a difference between the distribution of top wire fence heights on private lands and the distribution of top wire fence heights on public lands in our study area. We also calculated a 95% confidence interval on the median difference in top wire heights between the two land ownership categories.

### Categorical Correlation Tests

We tested if there were correlations between the six most common internal fence type variables (4-strand barbed wire, 5-strand barbed wire, woven wire, jack leg, 6-strand barbed wire, and 3-strand barbed wire) and the two land owner variables (private and public), as well as between fence type and land cover variables. We used a Pearson's Chi-squared Test for independence in R (R Core Team, 2019). We then examined the standardized Pearson residuals ($r$) to determine the nature of the dependencies between fence types and land ownership categories. Residual scores of $\pm 2$ indicated strong evidence against the hypothesis that the variables in that cell were independent (Agresti 2007). Correlations in the contingency tables with the largest absolute standardized residuals contributed the most to the total Chi-square score (Agresti 2007).

## Results

### Fence Location & Density Modeling

All four GIS fence location models showed comparable or better accuracy than Poor et al. (2014). All models had p-values for Kappa that indicated significant evidence against the null hypothesis that Kappa = 0 (prediction no better than chance), and accuracy scores were similar between models. The top GIS fence model was Model 3, which included undissolved private land tenure, public land tenure, croplands, and roads (Table 3). The Kappa scores of all accuracy tests for Model 3 showed moderate strength of agreement with ground truth data (Landis and Koch 1977) (Table 3).

The four models had the same road fence accuracy scores and similar total scores, but the 'undissolved private land with cropland' model (Model 3) and the 'undissolved private land without cropland' model (Model 4) performed better because they had the largest (and equal) internal fence Kappa scores (Table 3). The primary driver of internal fence accuracy was the assumption regarding fence locations along private property boundaries. Assuming each individual legal private parcel is fenced (what we termed 'undissolved') is more accurate than assuming all individual private parcels are fenced except for contiguous blocks of parcels that share boundaries and have the same owner, whereby only the outer combined boundary is fenced (what we termed 'dissolved'). Most fences in all models were internal fences, and given that road fence accuracy was the same, we were most interested in models with high accuracy scores for internal fences. By including the cropland fence layer in Model 3, we increased internal fence sensitivity (ability to predict true positives) but decreased specificity (ability to detect true negatives) over Model 4 (Table 3). Given the same internal fence Kappa scores, we selected the model with a higher internal fence sensitivity (Model 3) as the preferred model because all internal fence sensitivities were fairly low, whereas specificities were high (Table 3). We used Model 3 to estimate total fence length and fence density for Beaverhead and Madison Counties because it had the best performing internal fence predictions—as illustrated by the higher sensitivity score over Model 4—and true positives for internal fences were the most difficult to predict.

***Table 3***: *Accuracy assessment results for fence location GIS models. Model 3 performed best, though only slightly better than Model 4. It performed better because of a higher internal fence sensitivity score, indicating it was better at predicting true positives.*

| **GIS Fence Model 1 - Accuracy** | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| **Dissolved private land tenure + Public land tenure + croplands + roads** | | | | | | | | |
| | **Accuracy** | **Kappa** | **Kappa 95% CI** | **Kappa Z Score** | **Kappa P-value** | **Sensitivity** | **Specificity** | **Agreement** |
| **Roads** | 0.81 | 0.55 | 0.51 - 0.57 | 23.01 | <0.0001 | 0.84 | 0.74 | Moderate |
| **Internal** | 0.72 | 0.39 | 0.35 - 0.42 | 22.01 | <0.0001 | 0.48 | 0.89 | Fair |
| **Total** | 0.88 | 0.56 | 0.52 - 0.60 | 20.76 | <0.0001 | 0.90 | 0.75 | Moderate |

| **GIS Fence Model 2 - Accuracy** | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| **Dissolved private land tenure + public land tenure + roads** | | | | | | | | |
| | **Accuracy** | **Kappa** | **Kappa 95% CI** | **Kappa Z Score** | **Kappa P-value** | **Sensitivity** | **Specificity** | **Agreement** |
| **Roads** | 0.81 | 0.55 | 0.51 - 0.57 | 23.01 | <0.0001 | 0.84 | 0.74 | Moderate |
| **Internal** | 0.72 | 0.39 | 0.36 - 0.42 | 21.54 | <0.0001 | 0.44 | 0.93 | Fair |
| **Total** | 0.88 | 0.56 | 0.52 - 0.60 | 20.76 | <0.0001 | 0.90 | 0.75 | Moderate |

| **GIS Fence Model 3 - Accuracy** | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| **Undissolved private land tenure + public land tenure + croplands + roads** | | | | | | | | |
| | **Accuracy** | **Kappa** | **Kappa 95% CI** | **Kappa Z Score** | **Kappa P-value** | **Sensitivity** | **Specificity** | **Agreement** |
| **Roads** | 0.81 | 0.55 | 0.51 - 0.57 | 23.01 | <0.0001 | 0.84 | 0.74 | Moderate |
| **Internal** | 0.73 | 0.41 | 0.38 - 0.44 | 23.55 | <0.0001 | 0.53 | 0.86 | Moderate |
| **Total** | 0.89 | 0.56 | 0.52 - 0.60 | 20.88 | <0.0001 | 0.91 | 0.75 | Moderate |

| **GIS Fence Model 4 - Accuracy** | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| **Undissolved private land tenure + public land tenure + roads** | | | | | | | | |
| | **Accuracy** | **Kappa** | **Kappa 95% CI** | **Kappa Z Score** | **Kappa P-value** | **Sensitivity** | **Specificity** | **Agreement** |
| **Roads** | 0.81 | 0.55 | 0.51 - 0.57 | 23.01 | <0.0001 | 0.84 | 0.74 | Moderate |
| **Internal** | 0.73 | 0.41 | 0.38 - 0.44 | 23.22 | <0.0001 | 0.50 | 0.89 | Moderate |
| **Total** | 0.89 | 0.56 | 0.52 - 0.60 | 20.82 | <0.0001 | 0.91 | 0.75 | Moderate |

Internal fence layers, including the public land tenure, private land tenure, and cropland layers, were the most significant prediction layers in our top model because they comprised 83% of all modeled fencing (Table 4). Road fence predictions, though more accurate than internal fence predictions, accounted for only 17% of modelled fencing. Despite most of our study being comprised of public lands (63%), more fences were predicted on private lands (including croplands) than public lands (46% vs. 37%) (Table 4). Cropland land cover comprised only

964.8 km$^2$ of our study area, or approximately 0.04%, with a negligible amount located on public lands (16 km$^2$). Including predicted fences around croplands in Model 3 increased the model's interior fence sensitivity, though it did not change accuracy or Kappa scores from the same model without croplands (Model 4).

The top fence location GIS model (Model 3) predicted a total of 37,687 km of fences in Beaverhead and Madison Counites (Figure 2). This included 13,910 km of public land fences, 11,391 km of private land fences, 6,357 km of fences along roads and railroads (only 239 km were along railroads), and 6,029 km of fences around cropland land cover (Table 4). Beaverhead County had 4,298 km more public land fences than Madison County, which corresponded to its larger percent total area of public land than Madison County (Table 1). Beaverhead County had 1,458 km fewer combined private land and cropland fences even though it had slightly more total private land area than Madison County (4,465 km$^2$ v. 4,360 km$^2$). Additionally, the average size private parcel in Beaverhead County was 0.44 km$^2$ (108.7 acres), whereas the average size private parcel in Madison County was 0.28 km$^2$ (69.2 acres).

The US Forest Service lands had the largest share of predicted fences on public lands in both counties (35%), with 3,422 km in Beaverhead County and 1,488 km in Madison County. BLM lands had 2,894 km of fences predicted in Beaverhead County and 1,256 km of fences in Madison County. State lands had 2,297 km of fences predicted in Beaverhead County and 1,531 km of fences in Madison County. A combination of other government land ownership accounted for the remainder of 1,022 km of fences on public lands. Not all fences located on public lands are owned by the agency, as many are built and maintained by lessees.

***Table 4****: GIS model prediction of fence lengths for internal fences (public land tenure, private land tenure, and croplands) and road fences for Beaverhead and Madison Counties, Montana. Note: most cropland fences were also located on private lands.*

| Fence category | Estimated Fence Length (km) | | | |
|---|---|---|---|---|
| | **Beaverhead County** | **Madison County** | **Total** | **% Total** |
| Public | 9,104 | 4,806 | **13,910** | **37%** |
| Private | 5,066 | 6,325 | **11,391** | **30%** |
| Roads & Railroads | 3,238 | 3,119 | **6,357** | **17%** |
| Croplands | 2,915 | 3,114 | **6,029** | **16%** |
| **Total** | **20,323** | **17,364** | **37,687** | **100%** |

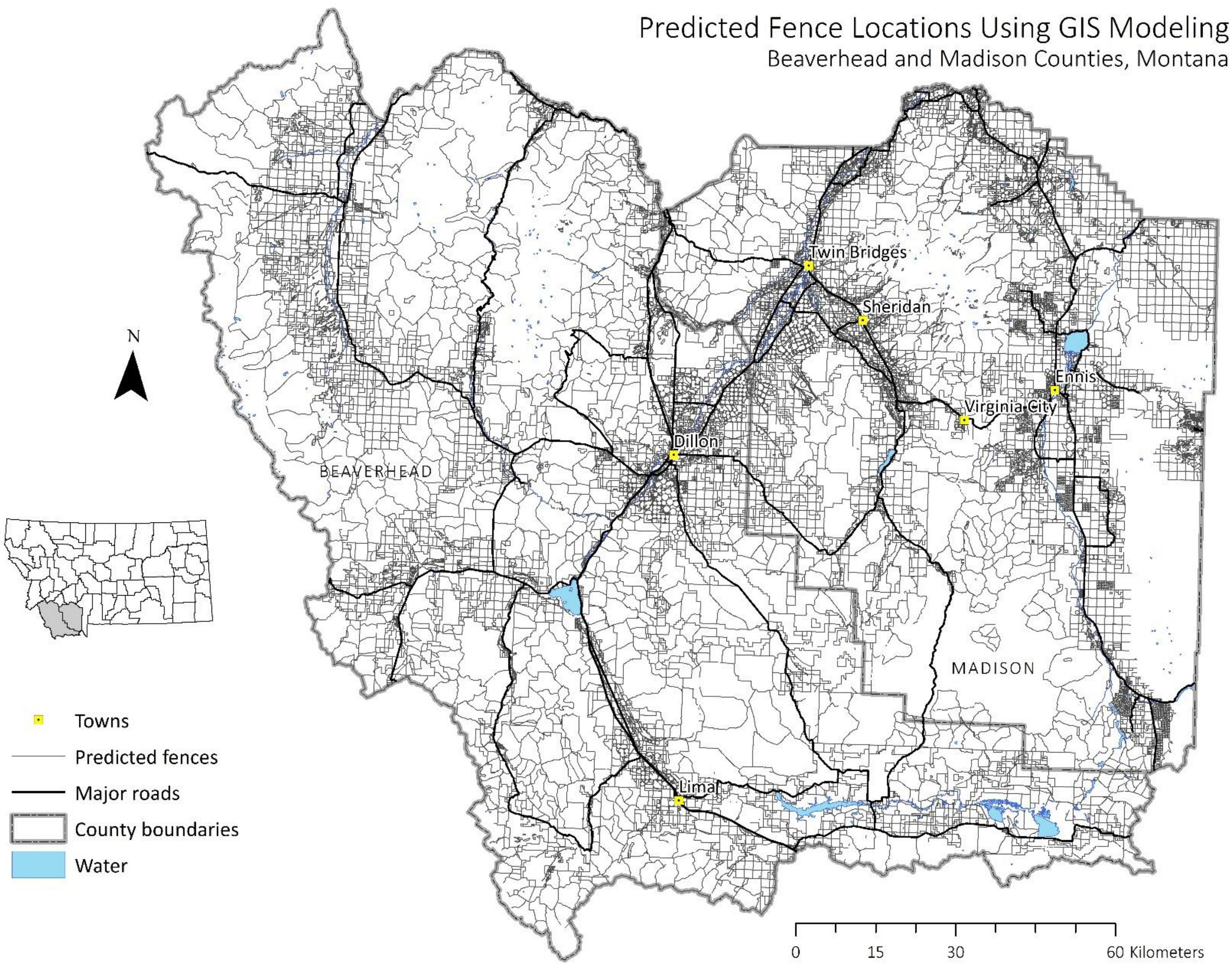


***Figure 2**: Top model of predicted fence locations in Beaverhead and Madison Counties, Montana, using a GIS of land tenure, roads, and land cover data. The fence model was moderately accurate (Kappa = 0.56) and predicted a total of 37,687 km of fences. Fences were modeled in ArcMap 10.6.1. Spatial reference is NAD 1983 State Plane Montana FIPS 2500.*

The mean fence density for the combined counties was 1.6 km/km$^2$ with a maximum density of 11.3 km/km$^2$ (Figure 3). Beaverhead and Madison Counties had an estimated mean fence density of 0.64 and 1.26 km/km$^2$ and a maximum density of 9.76 and 11.17 km/km$^2$, respectively.

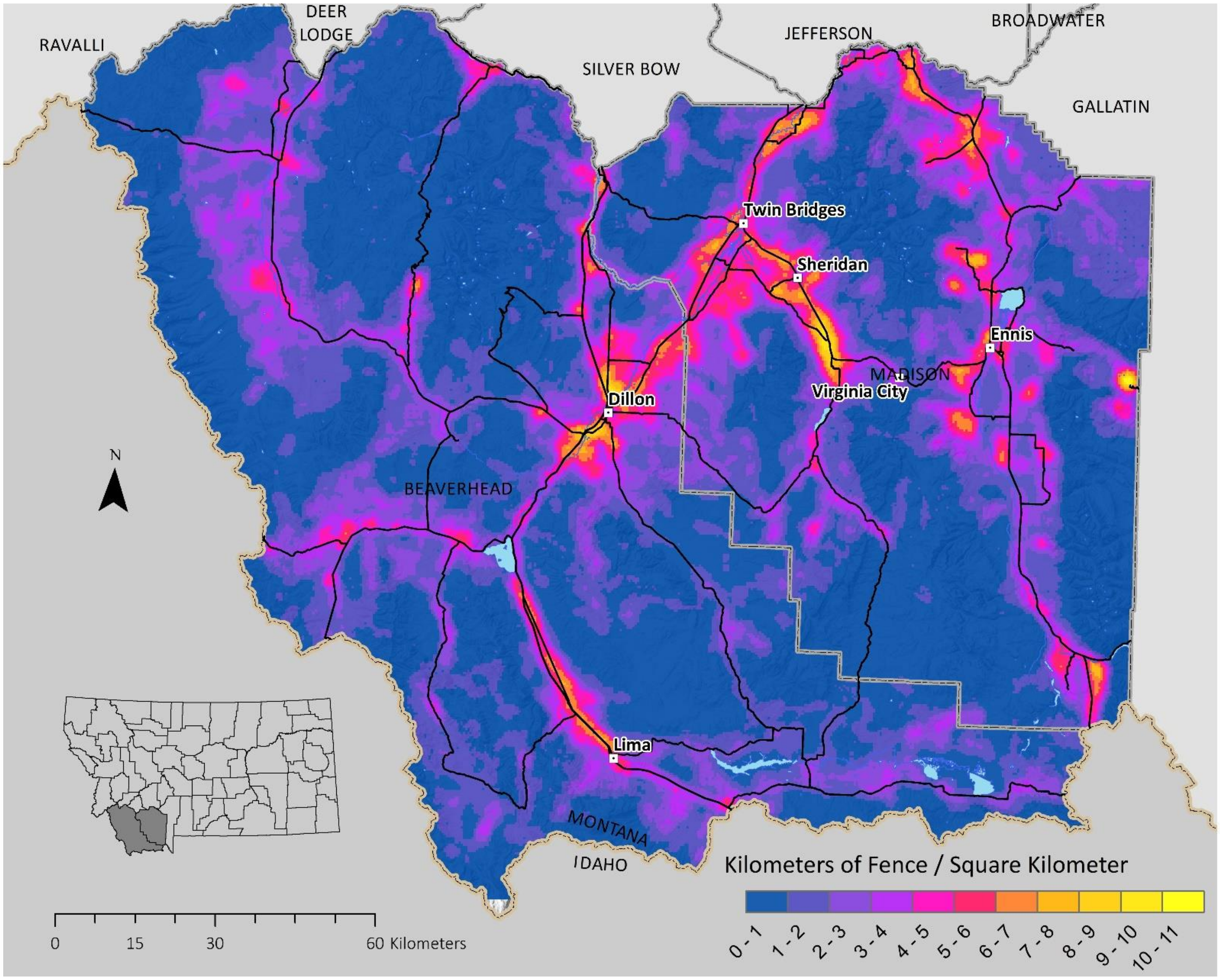


***Figure 3**: Modeled fence density in Beaverhead and Madison Counties, Montana. The mean fence density was 1.6 km/km$^2$ and the maximum density was 11.3 km/km$^2$. Fence density was modeled in ArcMap 10.6.1. Spatial reference is NAD 1983 State Plane Montana FIPS 2500.*

## Google Earth Fence Mapping & Accuracy Assessment

Manually digitizing fences using Google Earth was highly accurate in open land cover (Figure 4, Table 5 with Kappa values). Digitizing fences in forested land cover was impossible because fences were not visible using Google Earth imagery. For reference, the GIS fence model predicted 5,198 km of fences (13.8% of total modeled fencing) in forest land cover.

***Table 5:*** *Accuracy results for the Google Earth fence digitization map*

| Google Earth Fence Map - Accuracy | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | **Accuracy** | **Kappa** | **Kappa 95% CI** | **Kappa Z Score** | **Kappa P-value** | **Sensitivity** | **Specificity** | **Agreement** |
| **Roads** | 0.91 | 0.78 | 0.73 - 0.83 | 18.01 | <0.0001 | 0.89 | 0.94 | Substantial |
| **Internal** | 0.87 | 0.73 | 0.69 - 0.77 | 23.29 | <0.0001 | 0.80 | 0.92 | Substantial |
| **Total** | 0.93 | 0.76 | 0.71 - 0.81 | 16.32 | <0.0001 | 0.92 | 0.99 | Substantial |

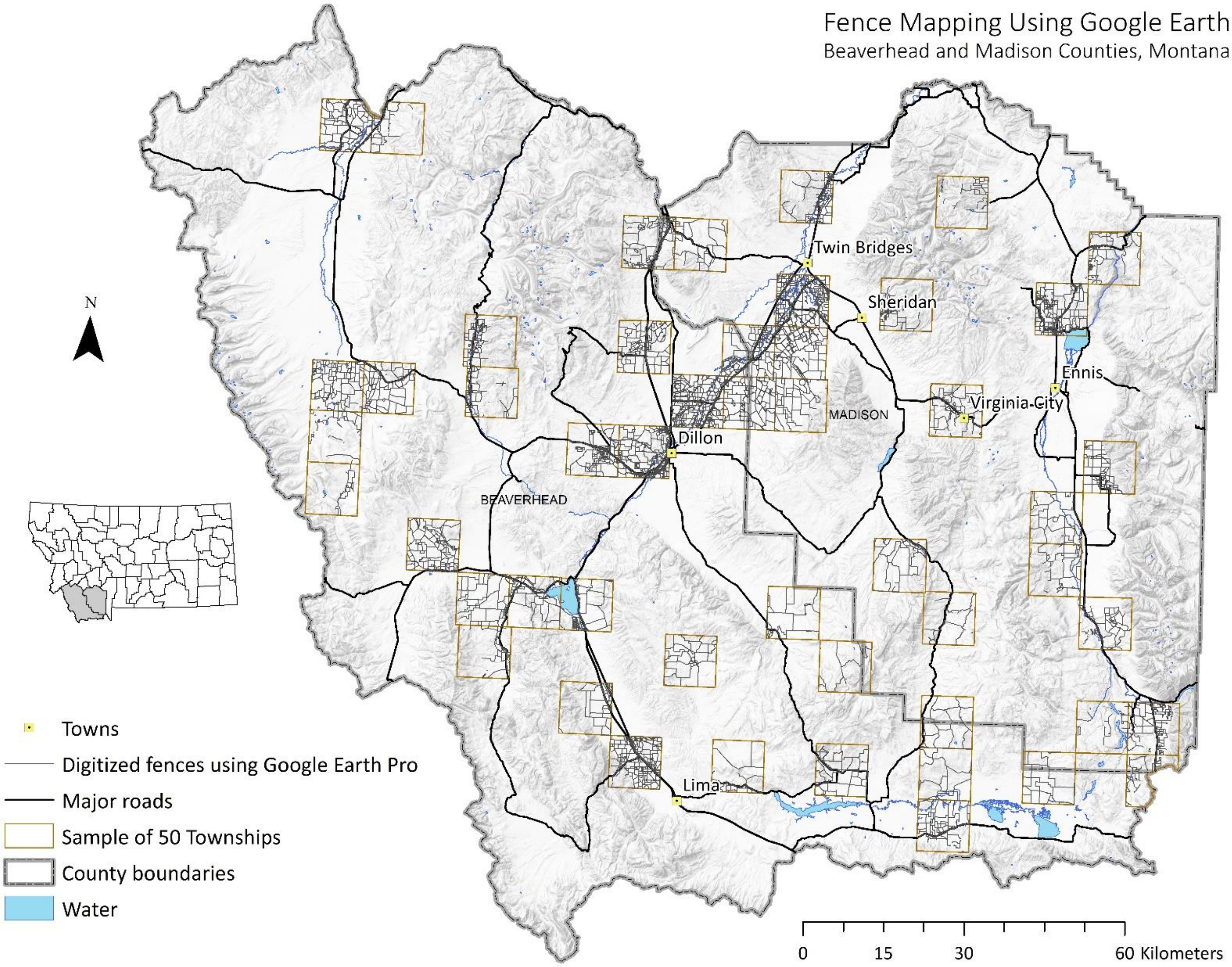


***Figure 4****: Fences manually-digitized in Google Earth Pro within a random sample of 50 townships in Beaverhead and Madison Counties, Montana. The map was highly accurate (Kappa = 0.76) in open land cover types. Fences were mapped in Google Earth Pro 7.3.3 and imported into ArcMap 10.6.1. Spatial reference is NAD 1983 State Plane Montana FIPS 2500.*

## Comparison of GIS Fence Modeling & Google Earth Fence Mapping

The GIS fence model showed improved results over previous iterations (Poor et al. 2014) and indicated moderate strength of agreement with ground truth data (Table 3). The Google Earth mapping technique was highly accurate in open land cover types only and had strong agreement with ground truth data (Table 5). The higher sensitivities and specificities of the Google Earth map indicated it was better than the model at distinguishing between fenced areas (true positives) and unfenced areas (true negatives). However, the potential weakness of the Google Earth mapping technique was illustrated by its inability to map fences in forested areas. It was also significantly more time- intensive than the GIS modeling approach. On average, it took 5 hours for an individual to complete manual digitization of fences using Google Earth for each complete survey township (Figure 5). Overall, it took approximately 5 months, or roughly 887 hours, to complete the GIS fence model for both Beaverhead and Madison Counties. In comparison, it took 1.5 months, or roughly 266 hours, to complete manual digitization of fences with Google Earth in 1/8$^{th}$ the area of Beaverhead and Madison Counties. At this rate, it would take approximately a year, or 2,128 hours, for one person at 1 FTE (40 hours a week) to complete a Google Earth fence map of both Beaverhead and Madison Counties.

The total length of fences manually digitized in non-forested areas using Google Earth in the 50-township sample was 6,810 km and the total length of fences modeled in the same area using the GIS approach was 8,984 km. The model predicted about 32% more fences than the Google Earth mapping method and had higher average densities. The Google Earth method had a mean density of 1.39 km/km$^2$ and a mean maximum density of 11.07 km/km$^2$ across the 50-township sample in non-forested areas. The GIS modeled fences across the same area had a mean density of 1.79 km/km$^2$ and a mean maximum density of 11.61 km/km$^2$. These results suggest that the GIS fence model overpredicted actual fence lengths and densities given the higher accuracy of the Google Earth method in non-forested areas.

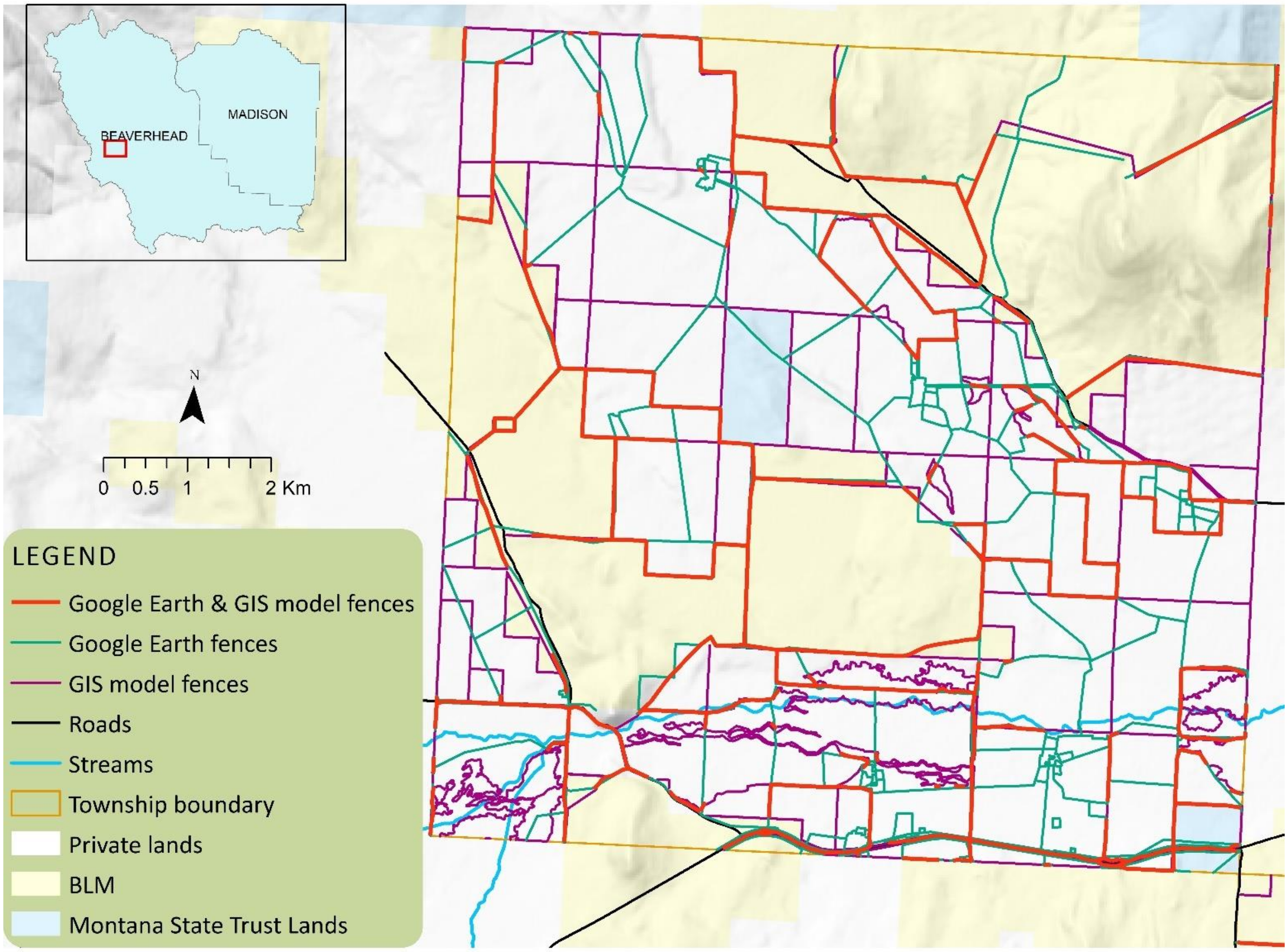


***Figure 5:*** *Comparison of manually-digitized fences using Google Earth and GIS modeled fences in a sample township in a non-forested area of Beaverhead County. Coincident fences within 30m are highlighted in red. Google Earth fence mapping was more accurate than GIS fence modeling in open land cover, though much more time intensive. The GIS modeling approach overpredicted fence length and density but remains a useful tool for estimating fences over large areas. Google Earth fence mapping is useful for identifying individual fences at smaller scales. Fences were hand-digitized in Google Earth Pro 7.3.3 and modeled in ArcMap 10.6.1. Spatial reference is NAD 1983 State Plane Montana FIPS 2500.*

## Fence Type Summary and Analysis

We sampled approximately 1,265 km of fences along roads and a total of 1,372 internal fence points, where each point represented a unique fence at its intersection with one side of the road. The most prevalent type of roadside fence was 5-strand barbed wire, which accounted for approximately 32% of all fence types along roads (Table 6). Approximately 97% of sampled road fences had an estimated bottom wire height less than 46 cm (18 in) from the ground and approximately 95% had an estimated top wire height greater than 102 cm (40 in). The most prevalent type of internal fence was 4-strand barbed wire, which accounted for 32% of the total count (Table 6). Approximately 97% of sampled internal fences had an estimated bottom wire height less than 46 cm (18 in) from the ground and approximately 94% had an estimated top wire height greater than 102 cm (40 in).

Of the 1,372 internal fence points, 1,130 were located on private lands and 242 were located on public lands. Of the 242 points located on public lands, 103 (43%) were located on BLM lands, 63 (26%) were located on Montana State Trust lands, 57 (24%) were located on Forest Service lands, and 19 (7%) were located on other government lands.

***Table 6****: Summary of type, length/count, and estimated bottom and top wire heights of sampled road-side and internal fences in Beaverhead and Madison Counties. Wildlife friendly fence specifications recommend a three- or four-strand barbed wire fence with a 46 cm (18 in) bottom-wire height and a 102 cm (40 in) top-wire height.*

| Sum of lengths/counts of fence type and estimated bottom and top wire heights for sampled road and internal fences | | | | |
|---|---|---|---|---|
| | **ROAD FENCE** | | **INTERNAL FENCE** | |
| **Fence Type** | **Length (km)** | **% Total length** | **Count** | **% Total count** |
| 5-strand barbed | 406 | 32% | 364 | 27% |
| 4-strand barbed | 344 | 27% | 434 | 32% |
| Woven | 293 | 23% | 259 | 19% |
| 6-strand barbed | 87 | 7% | 82 | 6% |
| 3-strand barbed | 51 | 4% | 79 | 6% |
| Jack leg | 49 | 4% | 93 | 7% |
| Electric | 21 | 2% | 37 | 3% |
| Other | 13 | 1% | 24 | 2% |
| **Total** | **1265** | **100%** | **1372** | **100%** |
| **Bottom wire height from ground (cm)** | **Length (km)** | **% Total length** | **Count** | **% Total count** |
| 0-13 | 321 | 25% | 277 | 20% |
| 13-25 | 515 | 41% | 512 | 37% |
| 25-38 | 296 | 23% | 408 | 30% |
| 38-51 | 123 | 10% | 163 | 12% |
| >51 | 10 | 1% | 12 | 1% |
| **Top wire height from ground (cm)** | **Length (km)** | **% Total length** | **Count** | **% Total count** |
| <94 | 15 | 1% | 18 | 1% |
| 94-107 | 456 | 36% | 493 | 36% |
| 107-119 | 479 | 38% | 567 | 41% |
| 119-132 | 264 | 21% | 218 | 16% |
| 132-145 | 32 | 3% | 38 | 3% |
| >145 | 19 | 1% | 41 | 3% |

## Bottom and Top Wire Heights of Internal Fences on Private v. Public Lands

The mean estimated bottom-wire height for internal private-land fences ($\bar{y}_1$ = 22 cm, SD = 13.8 cm) was 4.73 cm lower than the mean estimated bottom-wire height for internal public-land fences ($\bar{y}_2$ = 26.4 cm, SD = 13 cm) ($t$ = -4.73, P = 0.001, CI [-6.25, -2.58]). The median top-wire height for internal private-land fences ($m_1$ = 114.3 cm, IQR = 10.1 cm) was between 2.54 cm and

5.08 cm greater than the median top-wire height for internal public-land fences ($m_2$ = 106.68 cm, IQR = 10.16 cm) (p = 0.001, CI [2.54, 5.08]) (Figure 6). These small differences suggest that fences on public lands are not, on average, more wildlife-friendly than fences on private lands in our study. Top-wire sample means for both types of fences were close to wildlife-friendly specifications of 102 cm (Jones et al. 2018). However, bottom-wire sample means on private and public lands were both far lower than the 46 cm height recommendation for wildlife-friendly fencing (Jones et al. 2018).

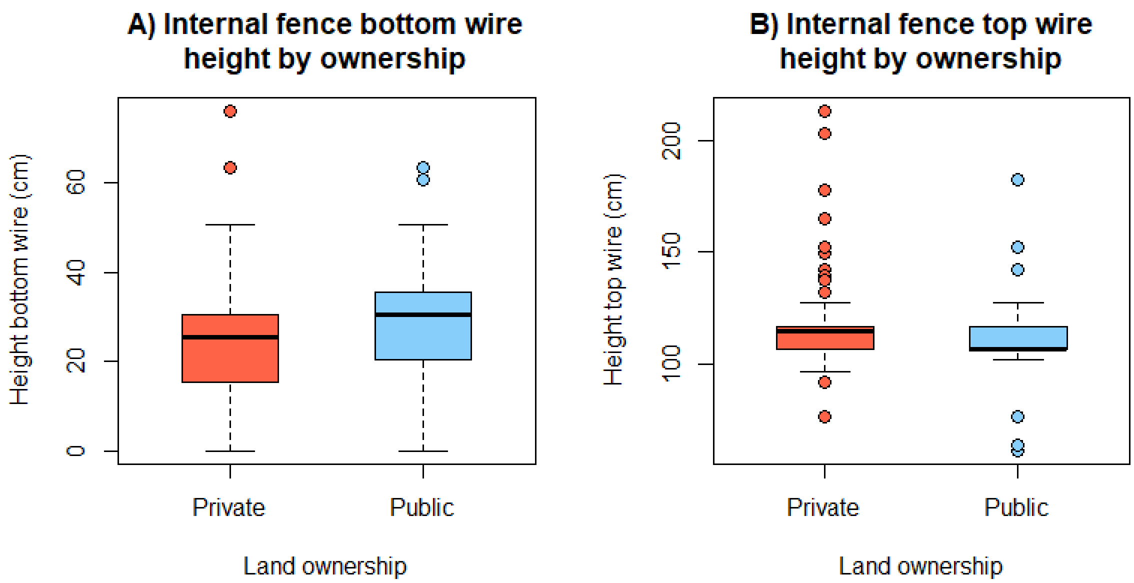


***Figure 6:*** *Sample data of estimated bottom-wire and top-wire heights of internal fences on private and public lands in Beaverhead and Madison Counties. Fences did not conform to wildlife-friendly specifications (46 cm bottom-wire height and 102 cm top-wire height) regardless of whether they were located on private or public lands.*

## Internal Fence Type Correlations with Land Ownership and Land Cover Type

Fence type and land ownership were correlated ($\chi^2$ = 45.52, df = 5, p = 0.001) (Figure 7). There was a strong positive relationship between 3-strand barbed wire and public lands ($r$ = 4.34), and a strong negative relationship between woven wire and public lands ($r$ = -2.56) (Figure 8). This latter finding was in line with expert opinion from BLM and Montana FWP staff that described agency efforts to replace woven wire with 3- or 4-strand barbed wire fences in recent years. However, woven wire fences still comprised 12% of the top six most common internal fence types found on public lands (Figure 7).

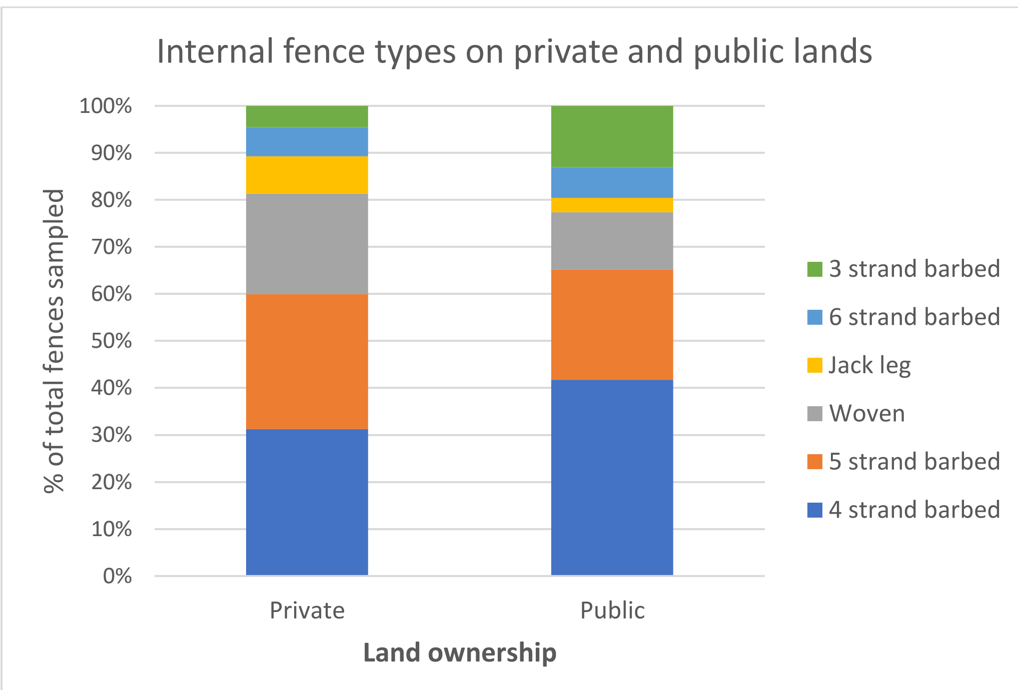


***Figure 7:*** *Proportions of the six most common internal fence types sampled on private and public lands in Beaverhead and Madison Counties. Fence type and land ownership type were correlated ($\chi^2$ = 45.52, df = 5, p = 0.001).*

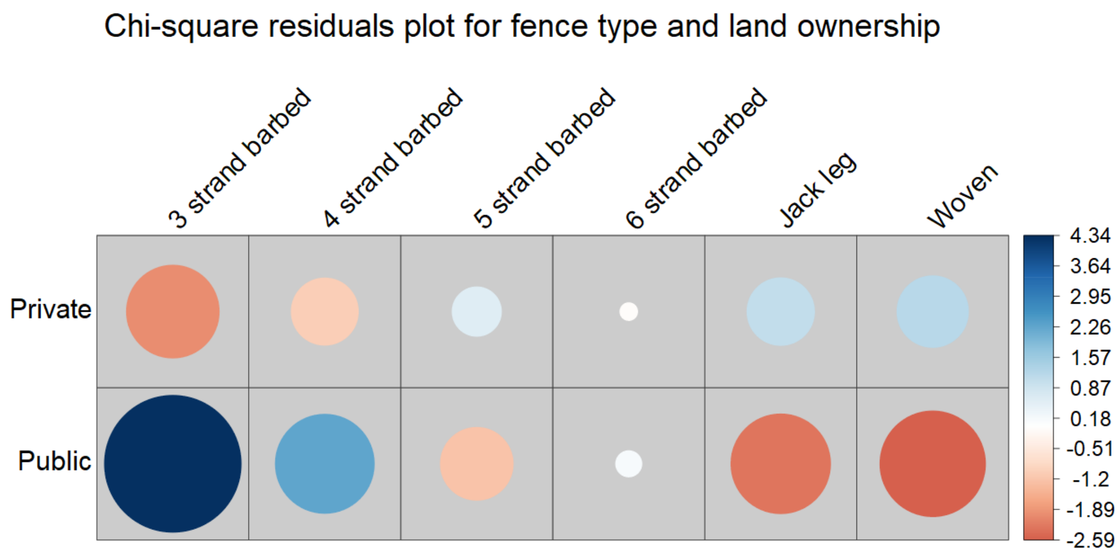


***Figure 8:*** *Positive (blue) and negative (red) residuals from the Chi-square test of independence for internal fence type and land ownership type. The size and color demonstrate the nature and strength of association between the variables. There was a strong positive association between 3-strand barbed wire and public lands and a strong negative association between woven wire and public lands.*

Fence type and land cover type were correlated ($\chi^2$ = 140.73, df = 15, p = 0.001) (Figure 9). Jack leg fences were most commonly found in riparian areas and rarely elsewhere (Figure 10). 3-strand barbed wire fences were most commonly found in shrubland and rarely elsewhere (Figure 10). Woven wire fences were most strongly associated with agricultural areas, which included cultivated croplands, native hay fields, and livestock pastures (Figure 10). 4-strand barbed wire was most strongly associated with shrubland, which was predominantly livestock rangelands (Figure 10). 5-strand and 6-strand barbed wire fences were found in almost equal proportions across all four land cover types (Figures 9, 10).

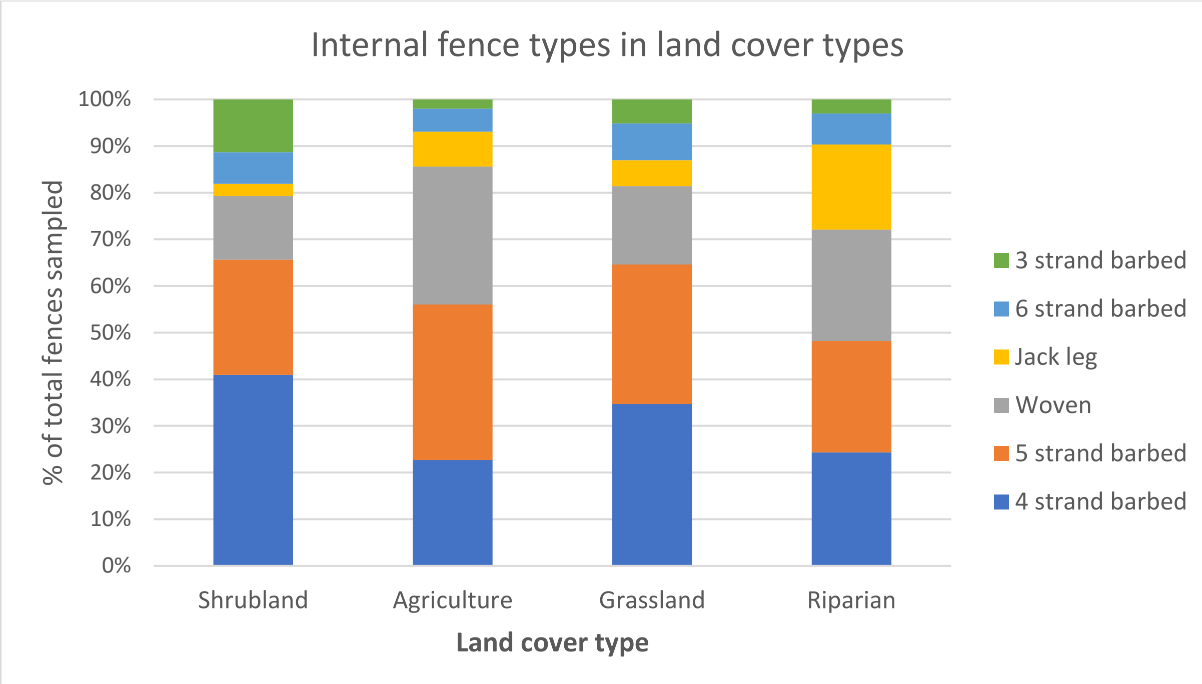


***Figure 9**: Proportions of the six most common internal fence types sampled in the four most common land cover types in Beaverhead and Madison Counties. Fence type and land cover type were correlated ($\chi^2$ = 140.73, df = 15, p = 0.001).*

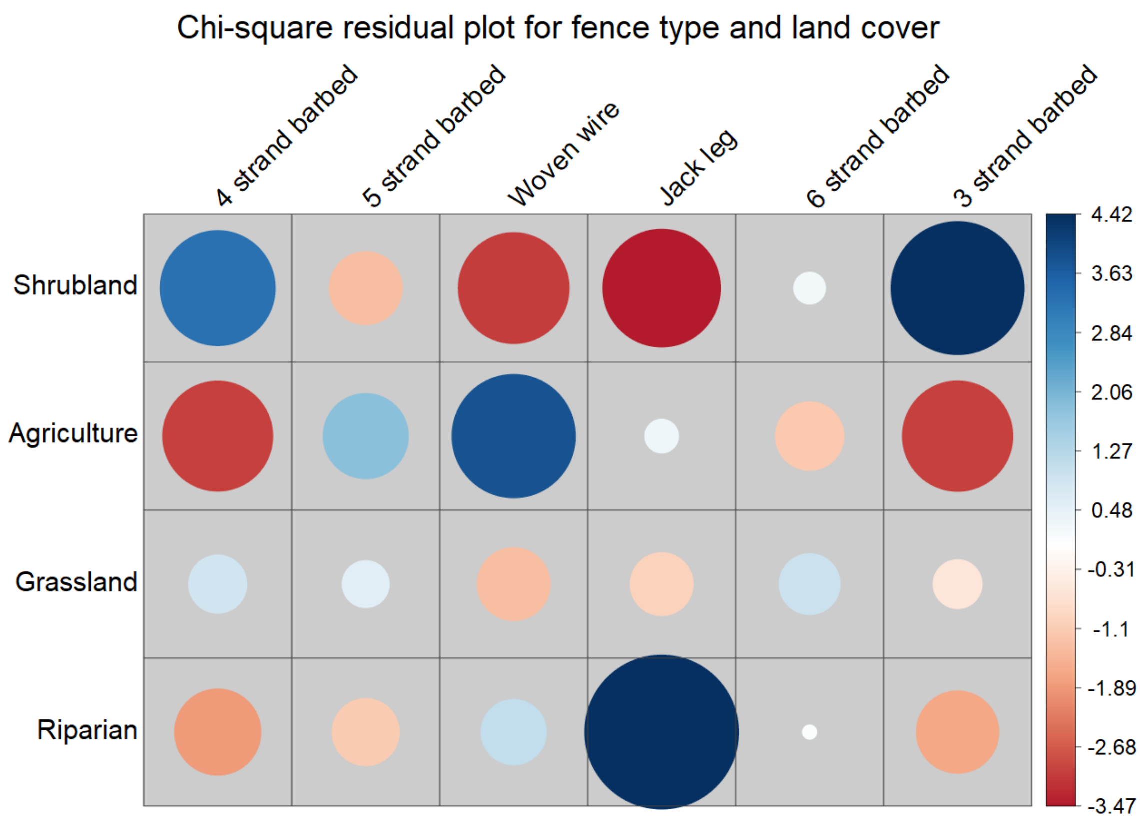


***Figure 10****: Positive (blue) and negative (red) residuals from the Chi-square test of independence for internal fence type and land cover type. The strongest positive association was between jack leg fence and riparian and the strongest negative association was between jack leg fence and shrubland.*

## Discussion

We demonstrated that a fence location and density GIS modeling approach using methods from Poor et al. (2014) could be adapted and applied to a new geographic region and achieve improved predictive accuracy (Poor et al. 2014). Our results increase confidence in the potential for widespread application of this type of predictive model to generate fence data across large regions as presented by McInturff et al. (2020). We also demonstrated that manual fence digitization using satellite imagery in Google Earth is a highly accurate method for mapping fence locations in open landscapes. The Google Earth mapping approach was more accurate overall but was considerably more time intensive than the modeling method. Further study is needed to determine whether efficiency of the Google Earth method can be improved and accuracy maintained by training computers to detect fence lines on high resolution satellite imagery through the use of software such as Google Earth Engine Python API. Even if efficiency can be improved, its inability to map fences in forested areas will likely remain a weakness, given that our model predicted over 5,000 km of fences in forested areas. Our results suggest that the GIS fence model can be used to estimate fence densities across large landscapes and identify focus areas where the Google Earth digitization approach can then be applied to refine fence locations in open land cover types at smaller scales. Our findings that fence bottom- and top-wire heights did not practically differ between public and private lands, and that mean bottom-wire heights were low, suggests fence mitigation projects are needed to improve landscape permeability for wildlife in our study area.

Predicting the locations of internal fences was challenging, and we demonstrated that a combined cropland and land tenure layer was a suitable method for internal fence predictions. Of the two types of layers that comprised our model (road fences and internal fences), road fences were more accurately mapped (Table 3). However, internal fences comprised 83% of our total modeled fences. Internal fence modeling was more complex than road fence modeling because it required combining private and public land tenure and land cover layers using a suite of assumptions (Poor et al. 2014). We improved model accuracy by assuming that all private parcels were fenced except in areas of cropland, where we assumed fences followed crop boundaries. Assuming all individual private parcels were fenced likely overpredicted fences in certain areas, particularly on large ranches where geographic variables like water and topography may influence fence placement more than parcel boundaries. Additionally, it is likely that not all private parcels were fenced in vacation home subdivisions, which were not masked out of our model in the same manner as towns. The public land tenure fence layer was likely the most accurate internal fence component because its assumptions received the most agreement between diverse groups of resource managers. There was also significant overlap between modeled fences and manually-digitized Google Earth fences on public lands in areas of open land cover (Figure 5).

One assumption from local experts that we were unable to accommodate in our model was that riparian areas likely had higher fence densities than non-riparian areas. However, in an inter-mountain system it is likely that private parcel density and roads are spatially correlated with riparian areas because human development tends to occur in valley bottoms where access and topography facilitate road construction and agricultural, residential, and municipal activities. Therefore, we likely inadvertently captured this assumption in our model with our road, cropland, and land tenure fence assumptions. Our density map of predicted fence locations reaffirmed this assumption, as high fence densities were located along river corridors, including the Big Hole, Beaverhead, Jefferson, Ruby, and Madison Rivers (Figure 3).

Our GIS fence model identified the highest fence densities (9 – 11 km/km$^2$) in the ex-urban and agricultural areas surrounding Dillon, as well as along river and highway corridors, such as along interstate I-15 in Beaverhead County and along highway 287 between Sheridan and Alder in Madison County (Figure 3). Other areas identified as having high fence densities were housing subdivisions, particularly in Madison county. One area showing high fence density that may be an outlier is the community of Big Sky, where housing density is relatively high, but few houses have fences because they are primarily vacation homes. Known vacation home housing developments may need separate assumptions in future model iterations to distinguish them from ex-urban hobby farm subdivisions where fences are likely, such as those surrounding Dillon. County zoning regulations and homeowner association (HOA) bylaws may be importance sources of information for generating these assumptions.

Overlaying animal movement data on our fence density raster to analyze habitat use probabilities and step-lengths will help determine if fence-sensitive species like pronghorn are avoiding high fence density areas and, if so, whether fences are reducing effective habitat in our study area (Jones et al. 2019). The results of our model suggest moderate confidence that smaller mean private parcel sizes correlate to more total fence length and greater fence density per unit area. For instance, Madison County had a smaller mean private parcel size, more total modeled fence length, and almost twice the mean fence density than Beaverhead County despite having less total private land area. With the potential caveat for vacation homes, we are likely to see more fences erected as rural parcels are subdivided. Pronghorn GPS collar data from the Madison Valley demonstrates annual migration activity between Ennis, Montana, and the Henry’s Lake area of Idaho (Montana Fish Wildlife and Parks unpublished data). Our density map highlighted high fence densities in the southern end of the Madison Valley that, in combination with topography, roads, and continued subdivision, may create a bottleneck effect restricting ungulate migration in the future (Berger 2004, Berger et al. 2008*a*, *b*, Harris et al. 2009, Seidler et al. 2015). There is a broad need for understanding how rate of change of fence construction effects ecological processes at multiple scales (McInturff et al. 2020), and Løvschal et al. (2017) provide methods for mapping fences using Landsat satellite imagery to document changes in fence presence and density over time (Løvschal et al. 2017). Our modeling approach could benefit from this temporal component to estimate fence density change by comparing historical cadastral ownership layers, especially in areas that are experiencing rapid subdivision. This temporal fence data could then be analyzed with wildlife movement to determine fence effects on habitat availability over time.

Fragmentation and other landscape changes due to human development are limiting wildlife movements globally, and loss of vagility affects population persistence and ecosystem processes such as predator-prey dynamics, nutrient cycling, and disease transmission (Tucker et al. 2018). Maintaining connectivity has thus become a major conservation and management goal across the globe (Crooks and Sanjayan 2006), especially in the face of a changing climate due to global warming (Krosby et al. 2010). Connectivity is a measure of how a landscape facilitates or impedes movement between resource patches (Taylor et al. 1993), and it is determined by both the makeup and distribution of structural components of a landscape as well as by functional responses of organisms to structural features (Drake et al. 2017). Fences are potential barriers that may impact functional connectivity for a variety of species, and their impacts can be assessed through resistance modeling (Sawyer et al. 2011). Our fence model can help approximate fence locations across the landscape for use in a connectivity model. Resistance surface values should represent all potential anthropogenic features that may affect movement, and in many areas the potential impacts of fences may be compounded by those of roads, and vice versa.

Our findings that highway corridors represented areas of high fence density are consistent with previous fence modeling efforts (Poor et al. 2014), and impermeable fence types in these areas likely pose significant obstacles to wildlife movement, thereby limiting connectivity. We observed woven wire fences with 0 cm bottom-wire heights topped with two strands of barbed wire and estimated top-wire heights of 121-132 cm paralleling both sides of interstate I-15 for approximately 135 km through Beaverhead County. This type of fence is particularly hazardous to ungulates (Harrington and Conover 2006). In addition, a railroad and frontage roads parallel the interstate and contribute an additional 2-4 sets of fences along its length. Although exclusion fences along highways can reduce vehicle collisions and wildlife mortality rates (Clevenger et al. 2001, Jaeger and Fahrig 2004), busy highways can act as barriers to wildlife movement by causing direct mortalities or avoidance behavior (Trombulak and Frissell 2000, Shepard et al. 2008, Seidler et al. 2015). By restricting movement, fenced highways can limit access to forage and important seasonal ranges and they can reduce genetic and functional connectivity (Holderegger and Di Giulio 2010). The fragmentation of populations by roads and other linear features can lead to loss of genetic diversity by restricting gene flow, increasing the likelihood of extinction (Epps et al. 2005, Marsh et al. 2008). Connectivity analyses using our fence model results can examine how fence densities along I-15 and other busy highways in our study area may contribute to the barrier effects of roads, especially when impermeable fence types are present. Furthermore, our fence location and density layers can be used in conjunction with other habitat and movement data to identify priority locations for wildlife crossing sites through this matrix of linear features to facilitate connectivity and avoid genetic isolation of populations

(Sawaya et al. 2014). Our Google Earth fence digitization approach can be used to identify individual fences that may be disproportionally affecting wildlife movement due to their placement location or construction type (as we demonstrate below for pronghorn). This fine-scale information is likely needed because in our interview process to generate fence assumptions we found that the Montana Department of Transportation does not maintain data on fences along roads (Montana Department of transportation personal communication).

These analyses must also consider the reality that building and maintaining connectivity corridors requires social and political will and funding (Dilkina et al. 2017). Dilkina et al. (2017) provide methods for connectivity modeling using resistance surface rasters and cost-benefit analyses to optimize corridor locations for multi-species movement between core areas that meet financial constraints. Carter et al. (2020) provide examples for integrating social perspectives, such as tolerance for wildlife presence, into connectivity modeling to increase the success likelihood of management actions (Carter et al. 2020). Fencing and roads are some of the primary linear features potentially impacting wildlife movements in our study area. Assessing their combined ecological effects and the potential for landowner engagement will help pinpoint the highest priority areas for application of limited conservation funding to increase landscape permeability.

Predicting fence types across landscapes is also key to understanding fence impacts on functional connectivity for a diversity of species because impenetrable fences may exist in low fence density areas. Determining fence type also helps inform management actions, as priority may be given to mitigating the most impermeable fences. This is a significant challenge and based in understanding and accounting for historic land use patterns and land cover correlations. Future modeling techniques could consider the livestock species rearing history or other agricultural history of a land parcel as a predictor of fence type. Fence type, specifications (such as bottom and top-wire heights), and placement are of particular concern in key seasonal range and migratory habitat of highly vagile species such as pronghorn and mule deer (Sawyer et al. 2013, 2016, Burkholder et al. 2018, Jones et al. 2018), and for particularly sensitive species such as sage grouse (Stevens et al. 2012). Our results suggesting fence type was correlated to land cover type demonstrates that future models could include a land cover prediction for fence type. Most notably, we found that woven wire, one of the least wildlife friendly fence types (Harrington and Conover 2006), was correlated to agricultural areas, which included hay fields (often used as livestock pastures) and irrigated crops. Species like pronghorn rely heavily on large expanses of native grassland and shrubland (Gates et al. 2012), but nevertheless, private agricultural areas become important winter range in an intern-mountain system where snow avoidance pressures animals into lower-elevation areas. Maintaining landscape permeability on winter range is likely a key component to long term population persistence and understanding the presence and distribution of fence types remains a key research need.

Our data collection efforts provided a novel baseline assessment of fence types in southwest Montana. Notably, we found that only 8% of sampled fences throughout Beaverhead and Madison counties had bottom wire heights that provided safe passage for pronghorn, indicated by a minimum of 46 cm (Jones et al. 2018). Though pronghorn are highly sensitive to low bottom wire heights, a bottom-wire height >= 46 cm increases movement opportunities for multiple ungulate species (Burkholder et al. 2018). Despite finding statistically significant evidence that mean bottom wire heights of internal fences on public lands were slightly higher than those on private lands, the difference had little practical significance because both sample means were well below wildlife friendly bottom wire specification recommendations of 46 cm.

Wildlife-friendly fence modifications are needed on both private and public lands in our study area to increase permeability. There is broad opportunity to develop policy initiatives to improve fencing to wildlife-friendly standards on publicly owned lands given that a significant number of fences were predicted on public lands and that fences were not wildlife-friendly. Private land fence modifications can be achieved by coordinating efforts between landowners and state, federal, private, and non-profit entities to create programs that support and incentivize wildlife habitat improvements on private lands. In areas where fence modifications are not possible, resource managers and other interested parties can work with landowners to apply temporary measures that may help improve permeability, such as leaving gates open in winter when some livestock pastures are not in use.

## Management Implications

We wanted to assess a real-world issue and look at wildlife-fence interactions and how understanding where fences are, and potentially their types, may help improve wildlife management. We overlaid pronghorn movement data for two females from January to August 2020 (Montana Fish Wildlife and Parks data sharing agreement) on our Google Earth fence map in an area of Beaverhead County identified as winter range for pronghorn. A map of a portion of our digitized fences and a subset of movement data illustrated how fences are restricting movement (Figure 11). A ground truth survey of the area identified abundant woven wire fences that likely pose challenges for pronghorn and juvenile elk and mule deer, especially during winter when snow may obstruct passage under the bottom wire at limited crossing locations (Harrington and Conover 2006, Jakes et al. 2018*b*). This area is a patchwork of private land, state land, BLM, and Forest Service, with many historic fences remaining unaltered.

Our mapping effort demonstrates the need for federal and state land managers and transportation authorities to not only consider fences as potential impediments in migration corridors, but as one of many factors that may influence the quality of winter and other seasonal range habitat.  Movement and resource selection analyses can employ our fence model or Google Earth fence map to quantify the impacts of fences on pronghorn behavior in this area (see Jones et al. 2019).  Additionally, state and federal agencies can conduct inventories of fences on seasonal ranges and apply removal and modification efforts to support desired habitat characteristics for wildlife conservation and management objectives.  We use pronghorn as an example, but this type of analysis can be used to inform management practices for a diversity of wildlife species.

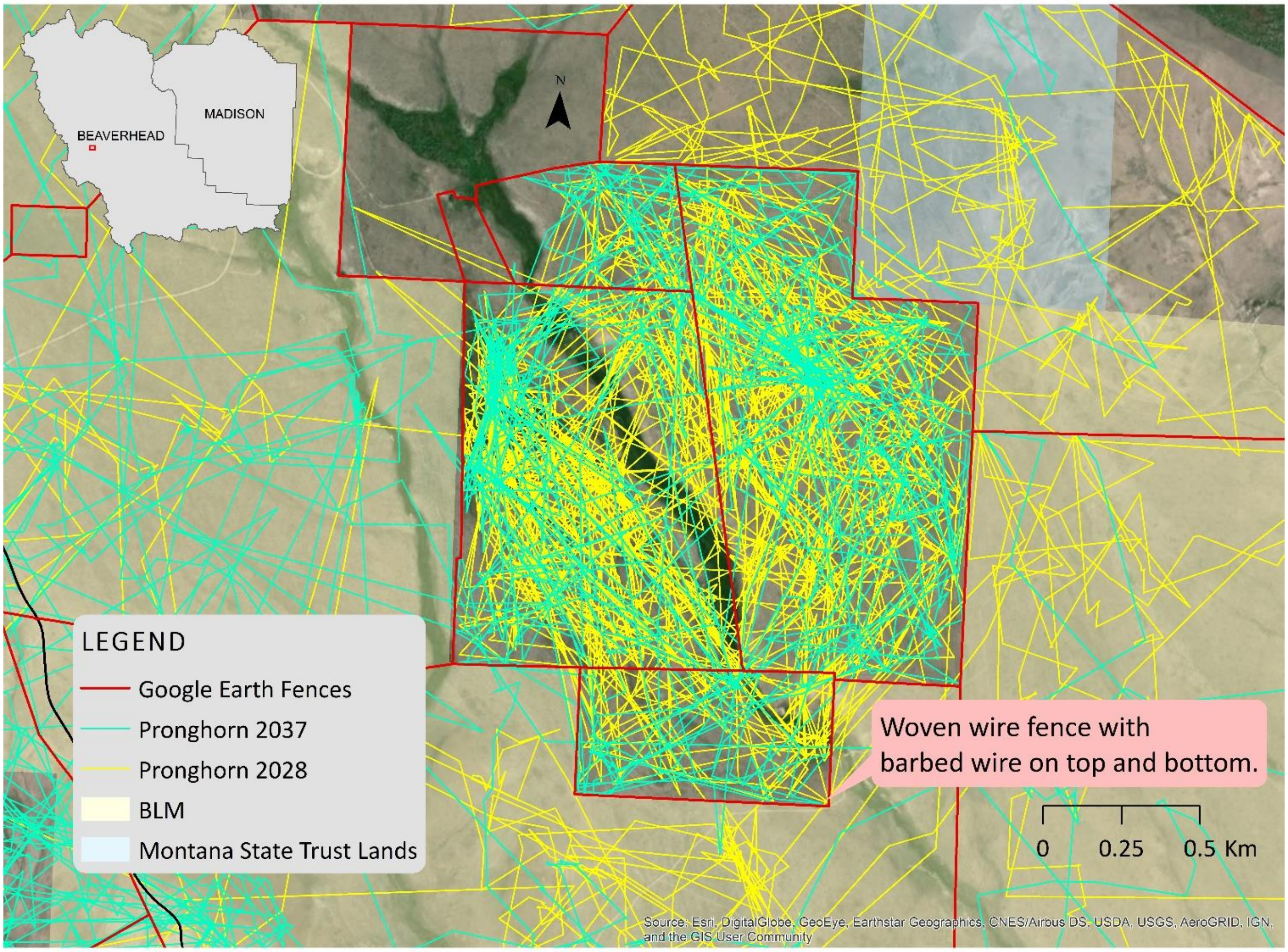


***Figure 61****: Manually-digitized fences in Google Earth are overlaid with pronghorn movement data to identify specific fences restricting movement. The tracks of two individuals appear to be significantly influenced by the cross-shaped fence outline in the center of the map. Ground truth surveys confirmed the presence of abundant woven wire fences that pose significant challenges for pronghorn. This tool is now informing a major fence mitigation project in this area to facilitate movement and improve seasonal range habitat quality for pronghorn.  Fences were hand-digitized in Google Earth Pro 7.3.3 then imported into ArcMap 10.6.1 with pronghorn movement data from 2020. Spatial reference is NAD 1983 State Plane Montana FIPS 2500.*

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## APPENDIX

**I.**

***Table 1:*** *Selection of random transect starting points by dividing initial sample in half while maintaining land cover/road type ratios.*

| Landcover | Number of transects | Number Unpaved | Number Paved |
|---|---|---|---|
| NoData | **20** | 8 | 12 |
| Riparian | **51** | 42 | 9 |
| Forest | **77** | 63 | 14 |
| Ag | **80** | 41 | 39 |
| Grassland | **146** | 118 | 28 |
| Shrubland | **318** | 277 | 41 |
| | 692 | 549 | 143 |

**"Number of Transects" above divided by 2 (rounded up) with road type ratios maintained**

| Landcover | Number of transects/2 | Number Unpaved | Number Paved |
|---|---|---|---|
| NoData | **10** | 4 | 6 |
| Riparian | **26** | 21 | 5 |
| Forest | **39** | 32 | 7 |
| Ag | **41** | 21 | 20 |
| Grassland | **73** | 59 | 14 |
| Shrubland | **160** | 139 | 21 |
| | **349** | 276 | 73 |

**II.**

***Table 2:*** *Road Fence (A) and Internal Fence (B) point layers used to collect fence data along transects using the Collector app for ArcGIS Online with a tablet. Sample data shown in fillable fields for each record.*

**A**

| **Road Fence** | |
|---|---|
| **TransectID** | 341 |
| **Heading** | W |
| **Left Fence Type** | Woven |
| **Left Height Bottom Wire** | 0 |
| **Left Height Top Wire** | 51 |
| **Left Maintenance** | M3 - Moderate |
| **Left Landcover** | Grassland |
| **Left Comments** | transformer station |
| **Right Fence Type** | Woven |
| **Right Height Bottom Wire** | 0 |
| **Right Height Top Wire** | 51 |
| **Right Maintenance** | M3 |
| **Right Landcover** | Grassland |
| **Right Comments** | |
| **TransectID Start** | 341start |
| **TransectID End** | |

**B**

| **Internal Fence** | |
|---|---|
| **TransectID** | 341 |
| **Fence Direction** | N |
| **Fence Type** | 4 strand barbed |
| **Height Bottom Wire** | 10 |
| **Height Top Wire** | 45 |
| **Maintenance** | M3 - Moderate |
| **Landcover** | Grassland |
| **Comments** | |

**III.**

**Fence Location Assumptions**

The GIS fence location model was informed by interviews and questionnaire responses from natural resources professionals in Beaverhead and Madison Counties. We developed a questionnaire and distributed it to 10 individuals at Montana Fish Wildlife and Parks, the Bureau of Land Management, the Montana Department of Natural Resources, the Natural Resources Conservation Service, the US Forest Service, the US Fish and Wildlife Service, and the Wildlife Conservation Society. These individuals' jurisdictions were in either Beaverhead or Madison County, or both.

We received a total of five completed questionnaires from BLM (3 responses), Montana Fish Wildlife and Parks (1 response), Montana Department of Natural Resources (1 response), and US Forest Service (1 response). We also interviewed individuals at the Beaverhead County Land Services Planning office, the Beaverhead County Museum, and the Montana Department of Transportation. All respondents noted that fence locations were difficult to predict on a scale of two counties and said there were many exceptions to the responses they provided. We reviewed the combined questionnaire and interview responses and evaluated personal observations from the field to create final assumptions.

**Road & Railroad Fence Assumptions**

All paved primary and secondary roads in Beaverhead and Madison Counties are fenced on both sides except for the following: the Pioneer Mountains Scenic Byway is only fenced along USFS pasture/allotment boundaries and private property; the portion of MT-43 within the Beaverhead-Deerlodge National Forest from the Montana/Idaho border at Chief Joseph Pass to where the road crosses Joseph Creek is not fenced; and the portion of US-287 located east of the junction with MT-87 within the Gallatin National Forest is not fenced. Paved local and paved "Off System" roads, as defined by MDT, have the same assumptions as unpaved public roads.

All unpaved public roads are fenced on both sides if traversing private lands. If an unpaved public road has private land on one side and public land on the other, the private side will be fenced but the public side will be fenced if the road follows a BLM or USFS pasture or allotment boundary or the boundary of State Trust, FWP, or USFWS lands. Unpaved roads traversing public lands are not fenced. If roads fencing falls within 5m of a fenced parcel boundary, the parcel boundary is removed to eliminate redundant fencing. This is a revision to assumptions in Poor et al. 2014. In an area assumed to have road fencing, it made more sense to erase the land tenure fence layer from the buffered road layer. The railroad traversing north-south through Beaverhead County parallel to Interstate 15 is fenced on both sides. These fences are coincident with the paved frontage road fencing and the I-15 fencing where the railroad is located between the two roads.

**Land Tenure Fence Assumptions**

BLM allotments and their interior pastures are fenced and supersede all other land tenure fence assumptions. When private, state, or other agency-owned parcels are contained within a BLM pasture or allotment, the pasture or allotment boundary is fenced but not the other property boundaries. BLM allotment boundaries replace BLM land boundaries, i.e. the allotment boundary is considered fenced and may extend past the BLM land boundary onto private lands or other public lands. In this case, the BLM land boundary is not fenced.

The USFS boundary around the Beaverhead-Deerlodge National Forest is fenced unless it is comanaged with other public allotments, primarily BLM. The Gallatin National Forest boundary is only fenced where it is consistent with allotment boundaries. Mining claims within USFS lands are generally not fenced, but private parcels within USFS lands are generally fenced along their boundaries. USFS allotments and pasture boundaries are fenced, except for eight sheep allotments and their corresponding internal pastures in the Gravelly Ranges. The USFWS lands in the Centennial Valley are fenced according to the shapefile fence layer provided by The Nature Conservancy.

Montana Fish, Wildlife, and Parks parcels are fenced along their boundaries, except for Wildlife Management Areas (WMAs) and parcels contained within USFS lands. WMAs are fenced along their boundaries regardless of ownership, but their borders with USFS lands are only fenced if they are consistent with allotment boundaries. Montana State Trust parcels are fenced along their boundaries unless the parcels are within BLM or USFS allotments or the parcels are included in the partial fence layer shapefile provided by the DNRC office in Dillon.

Private land parcels are fenced along ownership boundaries. Adjacent private property parcels with the same owner address will be combined so that the contiguous outer boundary is fenced. For example, if two adjacent parcels have the same owner address, we assume one boundary fence encloses both parcels but make no assumptions regarding the location of interior fences (except for crops and hayfields, see below). No evidence suggests that interior fences always follow section or other lot lines if adjacent parcels have the same owner. Fences are assumed to follow property boundaries in urban areas. All towns and census-designated communities are considered to have high fence densities.

## Land Cover Fence Assumptions

The outlines of cultivated crops and hay fields are fenced regardless of ownership. Riparian areas are estimated to have higher fence density than non-riparian areas, but no county-wide assumptions can be made concerning where fences are located in the riparian zone (that are not already covered by other assumptions).

## Fence Type Assumptions

In general, on BLM and USFS lands, allotment boundaries are fenced with 4-strand barbed wire and pasture boundaries are fenced with 3-strand barbed wire. On Montana Fish Wildlife and Parks and State Trust lands there is little remaining woven wire. Most fences on these lands are barbed wire but the number of strands varies widely.